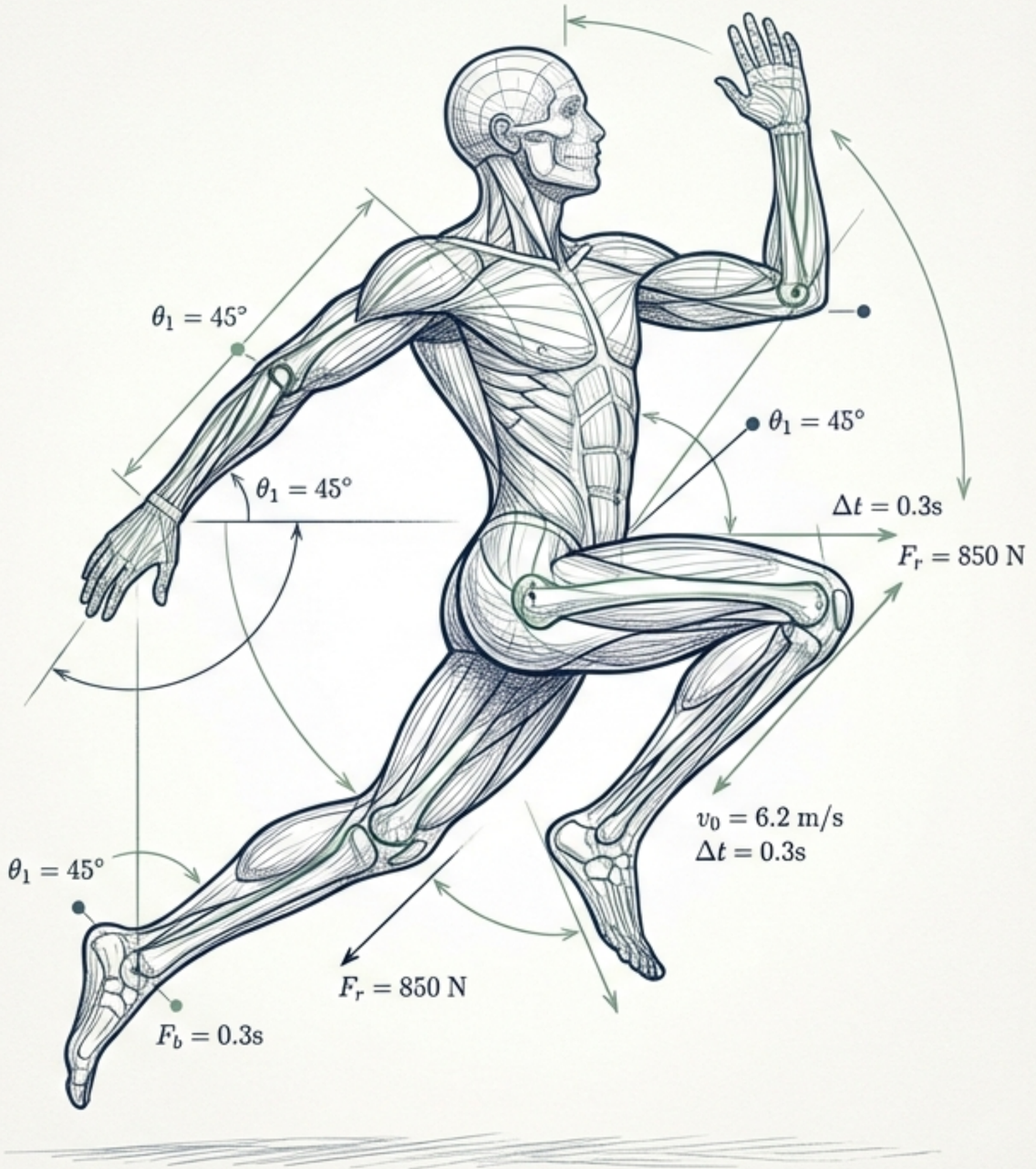
Modeling Complex Relationships in Movement Science

Human movement rarely depends on a single factor. Athletic performance, injury risk, and physiological responses emerge from multiple interacting variables that require advanced statistical tools to decode.



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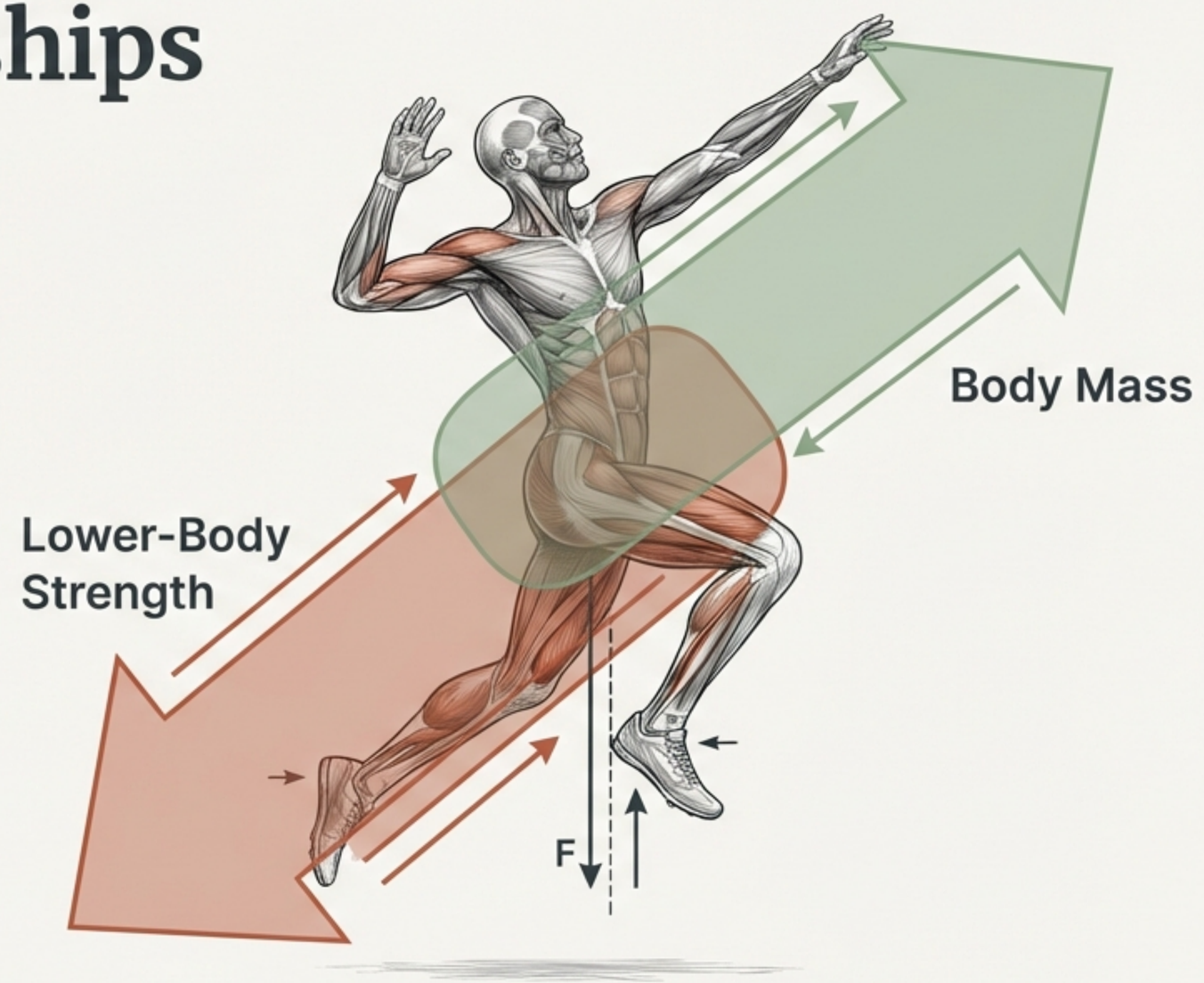
Moving Beyond Simple Bivariate Bivariate Relationships

Predicting complex outcomes requires tools that can handle multiple overlapping factors. Vertical jump height depends heavily on both lower-body strength and body mass.

Because stronger athletes also tend to be heavier, a simple bivariate correlation conflates the direct effect of strength with the indirect effect of mass.

Multiple regression solves this by modeling two or more predictor variables simultaneously to disentangle their unique contributions.



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Deconstructing the Multiple Regression Equation

$\hat{Y}$: The model estimates the predicted value of the single continuous outcome variable.

Holding Constant: The model isolates independent contributions by estimating each coefficient from only the variance unique to that predictor, holding all other variables constant.

$$\hat{Y} = b_0 + b_1X_1 + b_2X_2 + \ldots + b_kX_k$$

b_0: The intercept represents the baseline predicted outcome when all independent predictors equal zero.

b_k: Each regression coefficient represents the unique change in the outcome for a one-unit increase in its corresponding predictor.

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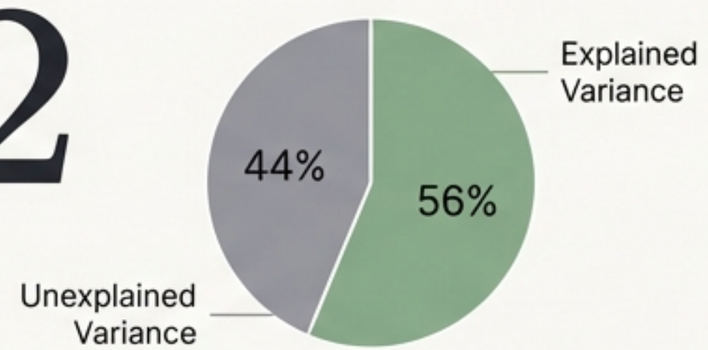
Quantifying the Predictive Power of the Model

R

The multiple correlation coefficient (R) quantifies the overall strength of the relationship between the observed values and the model's predicted values.

R^2



The coefficient of determination (R^2) represents the exact proportion of total variance in the outcome variable that is successfully explained by the full set of predictors.

The remaining variance is left unexplained and is attributable to unmeasured variables, random error, or processes the model fails to capture.

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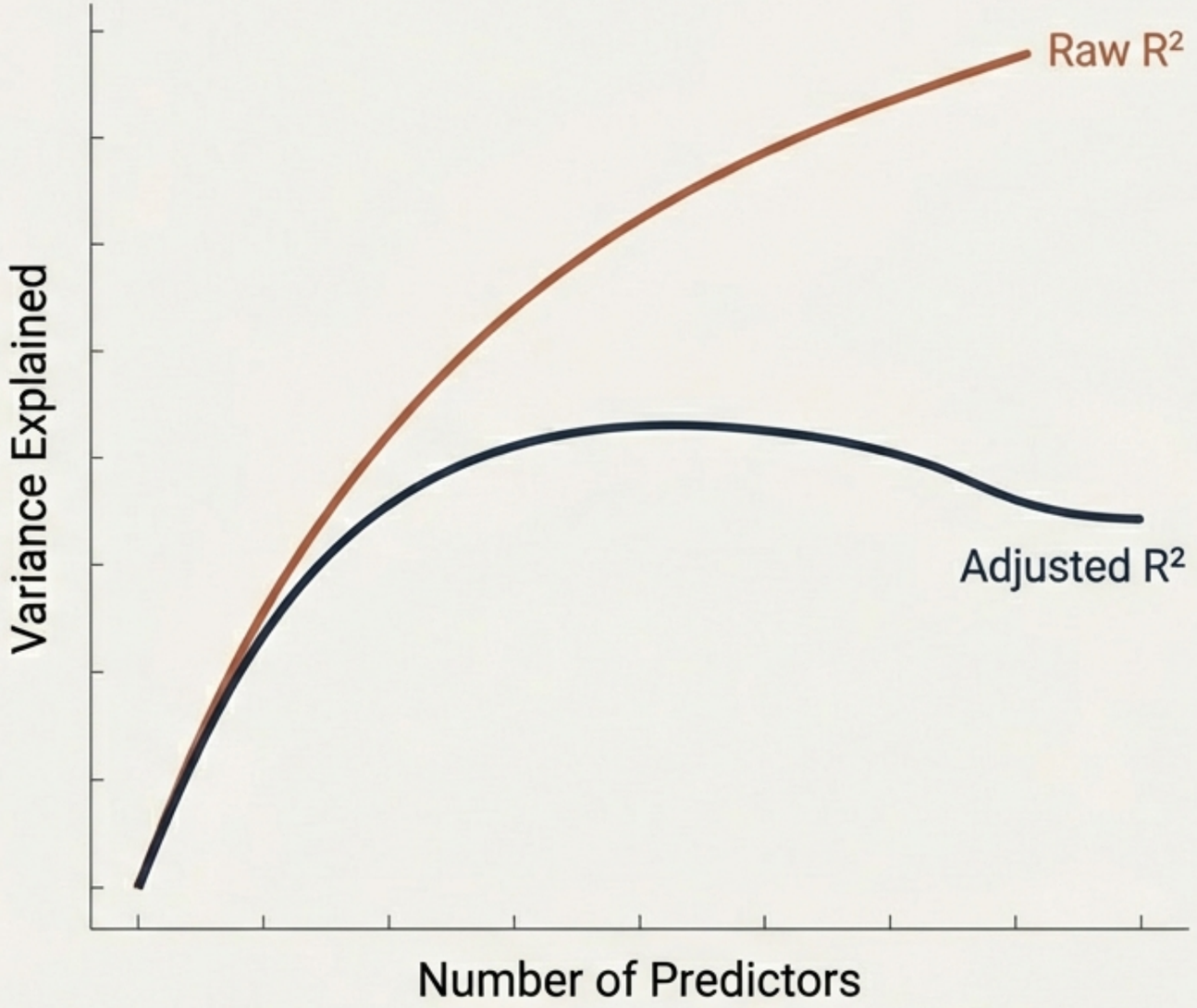
Avoiding the Overfitting Trap with Adjusted Metrics

Adding any new predictor to a model will mathematically increase raw R^2, even if the variable consists entirely of random sample noise.

This illusion of improvement creates overfitting, where models fit sample-specific quirks rather than generalizable, real-world patterns.

Adjusted R^2 provides a necessary correction by actively penalizing by actively penalizing the model for every included predictor that fails to contribute meaningfully to the explained variance.



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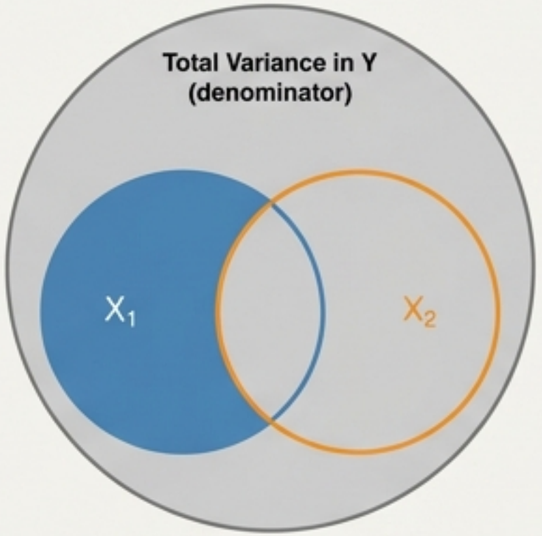
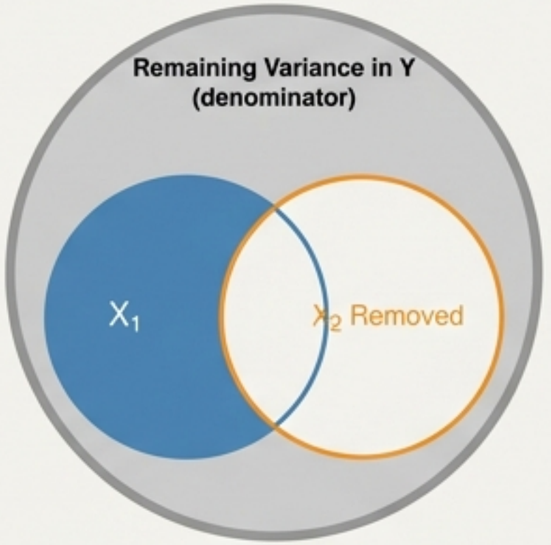
Disentangling the Overlap Between Individual Predictors

Semipartial (Part) Correlation



$$r^2_{semi} = \frac{\text{Unique Variance of } X_1}{\text{Total Variance of Y}}$$

Partial Correlation



$$r^2_{partial} = \frac{\text{Unique Variance of } X_1}{\text{Total Y Variance minus } X_2}$$

Partial correlation compares a predictor's unique contribution against only the remaining unexplained variance after the influence of other variables has been stripped away from both.

Semipartial correlation measures a predictor's unique contribution against the entire total variance of the outcome variable.

Squaring the semipartial correlation (ΔR^2) reveals exactly how much additional variance the predictor adds to a model that already contains the other variables.

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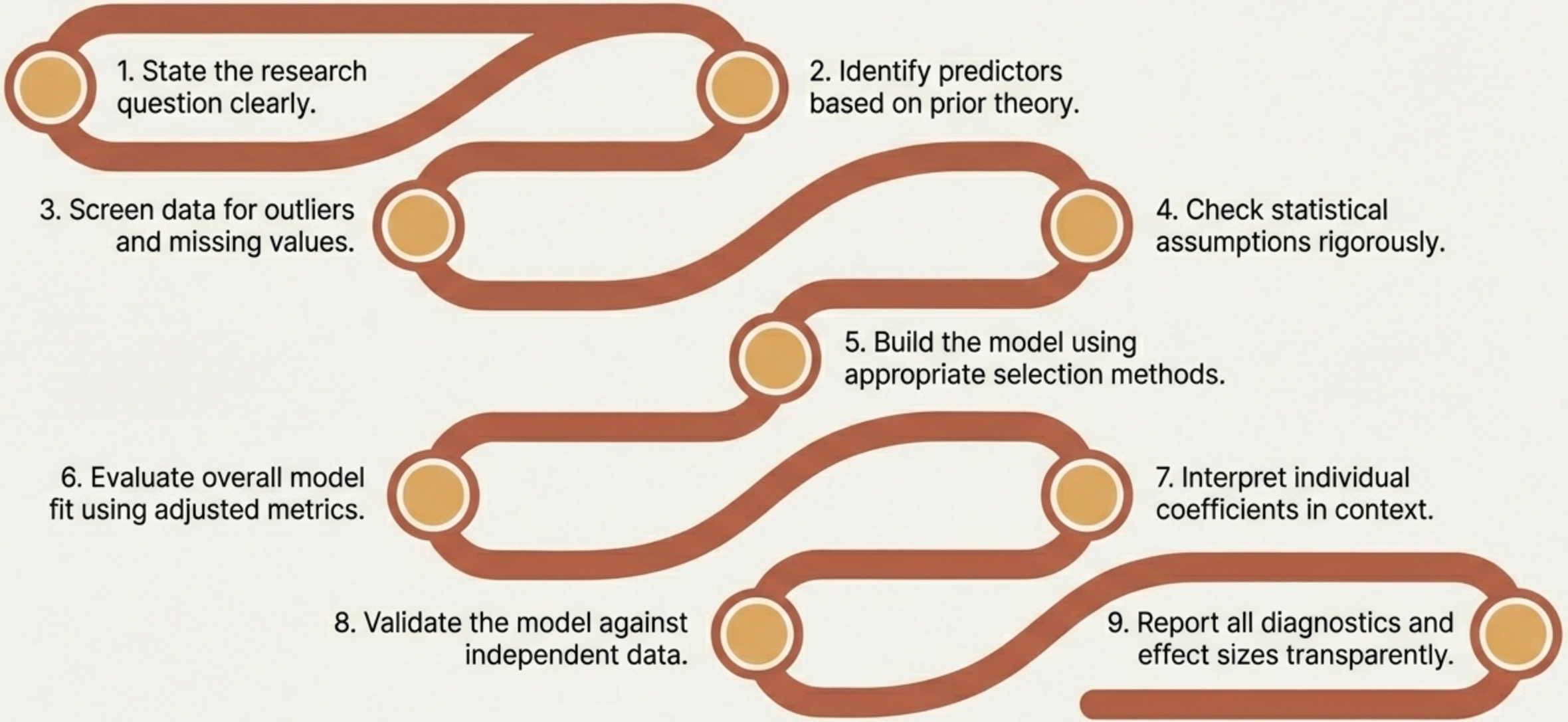
Executing the Complete Analysis Lifecycle


1. State the research question clearly.
2. Identify predictors based on prior theory.
3. Screen data for outliers and missing values.
4. Check statistical assumptions rigorously.
5. Build the model using appropriate selection methods.
6. Evaluate overall model fit using adjusted metrics.
7. Interpret individual coefficients in context.
8. Validate the model against independent data.
9. Report all diagnostics and effect sizes transparently.

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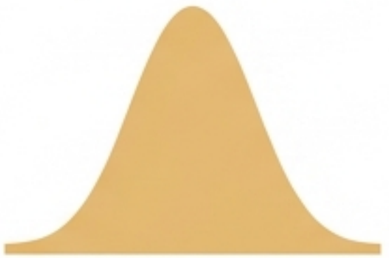
Verifying Core Statistical Assumptions

Linearity requires the effect of each predictor on the outcome to follow a straight-line pattern rather than a curved relationship.

Independence dictates that each observation must be entirely separate, meaning data cannot come from repeated measures on the same athlete.

Homoscedasticity mandates that the spread of the residuals remains roughly equal across all levels of the predicted values.



Normality of residuals requires the differences between observed and predicted values to follow a standard bell curve distribution.

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Diagnosing and Resolving Multicollinearity

Multicollinearity occurs when predictors are so **strongly intercorrelated** that the model cannot successfully distinguish their **separate effects**.

This redundancy **inflates standard errors** and causes truly important predictors to **appear statistically nonsignificant**.

The Variance Inflation Factor (VIF) quantifies this instability, with values exceeding ten requiring immediate **intervention**.

Researchers must resolve severe **multicollinearity** by removing redundant predictors or combining them into single composite variables.

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Translating Output into Practical Interpretations

		Unstandardized (b)	Standardized (β)	t-value	Sig.
1	Constant	12.000		12.403	.000
	Predictor 1	0.3000	0.3000	4.439	.000
	Predictor 2	0.0000	0.0000	3.370	.395

b

Unstandardized coefficients (b) measure effects in the exact original units of the data, making them essential for practical, real-world prediction.

β

Standardized coefficients (β) recalculate these effects into standard deviation units, allowing researchers to directly compare the relative strength of predictors measured on entirely different scales.

A comprehensive analysis always reports both metrics to capture both practical application and relative variable importance.

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Evaluating Statistical Significance at Two Levels

The omnibus F-test evaluates whether the entire model predicts the outcome significantly better than a null model relying solely on the intercept.

Individual t-tests subsequently determine whether each specific predictor adds **significant, unique value** independent of the rest of the model.

A predictor can achieve strict statistical significance but remain practically trivial, making it crucial to examine confidence intervals and standardized effect sizes.

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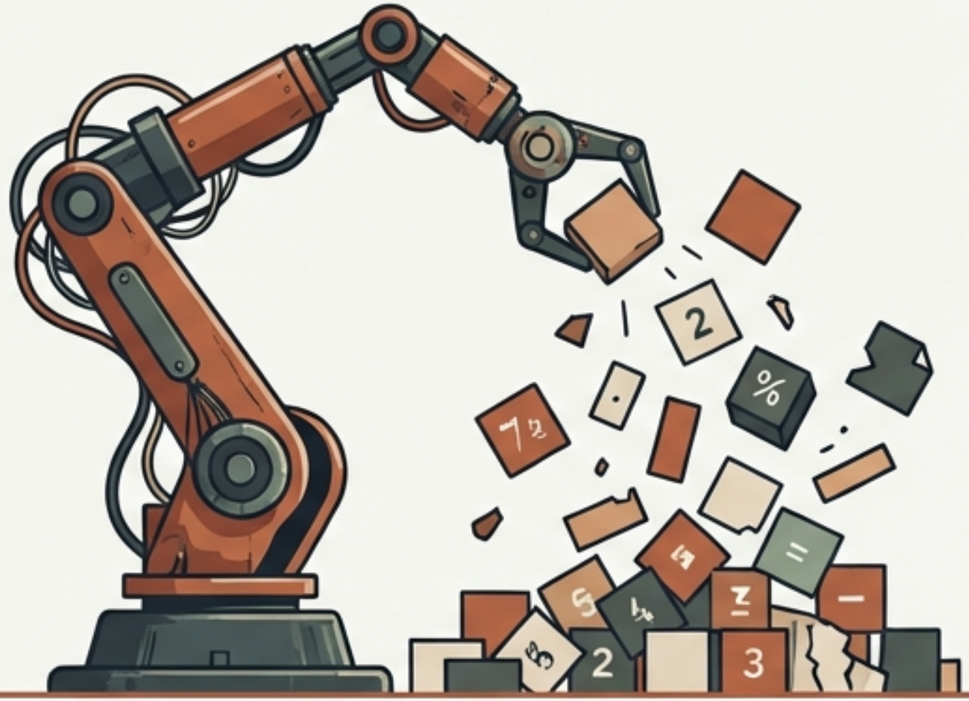
Choosing Predictors with Scientific Rigor

Theory-Driven Selection

Selecting predictors based on prior research, theoretical frameworks, and domain expertise protects against overfitting and ensures the results remain interpretable.

Automated Stepwise Regression



Including every available variable creates bloated models that suffer from multicollinearity and fail to generalize beyond the immediate sample.

Automated stepwise regression algorithms capitalize on random sample noise to select variables, leading to inflated error rates and unreliable models.

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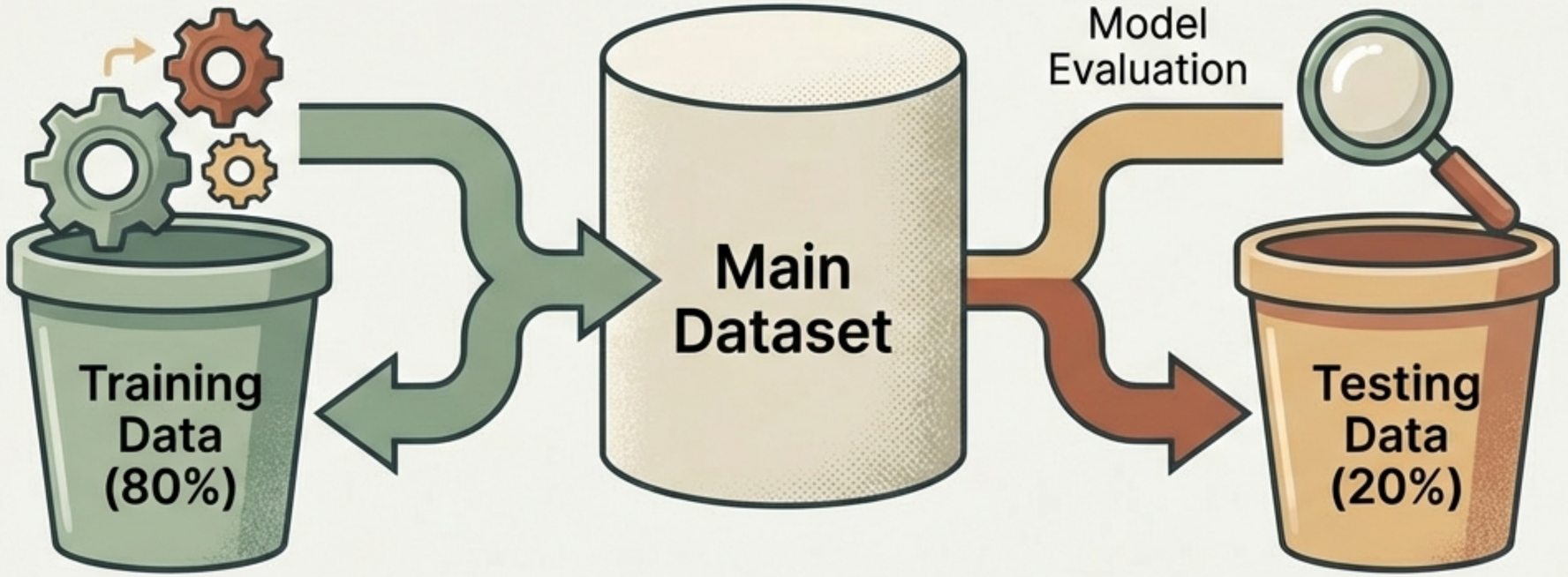
Validating the Model Against the Real World



A regression model that performs exceptionally well on its original data may fail completely when applied to a new population.

Cross-validation repeatedly splits the data into training subsets and testing subsets to estimate how well the predictions will generalize.

The gold standard requires fitting the model on one sample and testing it on a completely independent validation sample to predictive shrinkage.

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Reporting Results with Complete Transparency

Clear and complete reporting allows readers to evaluate the evidence, reproduce the analysis, and judge whether the effects are practically meaningful.

A comprehensive APA-style summary must explicitly state the overall model fit metrics alongside the F-statistic and its corresponding p-value.

The results must break down every individual predictor by reporting its unstandardized coefficient, standard error, standardized coefficient, and 95% confidence interval.

Diagnostic checks validating the absence of severe multicollinearity should be explicitly noted to confirm model stability.

A multiple regression model predicting vertical jump height from lower-body strength and body mass was significant, $F(2, 47) = 30.2$, $p < .001$, $R^2 = 0.56$, adjusted $R^2 = 0.54$. Both predictors contributed significantly: strength ($b = 0.20$, $SE = 0.03$, $\beta = 0.58$, $t = 5.8$, t, $p < .001$, 95% CI [0.13, 0.27]) and body mass ($b = -0.10$, $SE = 0.04$, $\beta = -0.25$, $t = -2.5$, $p = .016$, 95% CI [−0.18, −0.02]). VIF values were < 2.5, indicating no multicollinearity concerns.

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Final Limitations and Cautious Best Practices

Multiple regression successfully identifies complex associations but cannot inherently prove causal relationships between biomechanical variables.

Predictions become entirely unreliable when extrapolated outside the specific ranges of the observed data used to build the model.

Models require adequate sample sizes to remain mathematically stable, adhering to a general rule of at least ten to twenty observations per predictor.

Responsible modeling requires discipline, deep domain knowledge, and a commitment to transparently reporting both successes and diagnostic limitations.

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